THE TRENDS IN CONSTRUCTION OUTPUT FORECASTING STUDIES OVER THE LAST 25 YEARS

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Abstract
Construction output forecasting plays a crucial role in developing strategic plans for the construction industry. Various techniques have been used for construction output forecast research which includes: regression, artificial neural network and structural models, just to mention a few. An up-to-date systematic review of previous studies focused on construction output forecasting will provide insights into the current state of knowledge and gaps in the field. A three-step method was used to obtain relevant publication (15 papers met the inclusion criteria) and to compile a database of techniques and findings. It was found that statistical model is the most dominant method used to forecast construction output data. Four research gaps were identified in the review process. Continued efforts are needed to explore the application of artificial intelligence (AI) models in construction output forecast research. This can be attributed to the accuracy and reliability associated with the AI models in previous studies. Accurate construction output forecast is vital to the sustained growth of the construction industry.

Keywords: Construction industry, Construction output, Forecasting techniques, Systematic review

1 Introduction

The construction industry plays a pivotal role in the economic development process of any nation. Commentators have argued that the construction industry has strong links with the economy. Empirical evidence has shown that the construction industry output (hereafter termed construction output) tends to fluctuate with economic cycles (Chan, 2002, Goh, 2005, Lewis, 2004). Fluctuations in construction output create inefficiencies in the production process (Ofori, 1993; Ofori et al., 1996), bankruptcy and retrenchment within the construction industry during periods of low production (Jiang et al., 2013, Ng et al., 2008a). These fluctuations have detrimental effects on the construction industry and the economy in general. In addition, macrolevel studies aimed at improving the construction industry have suggested the need for predictive models to aid long-term forward planning (Egan, 1998, Ng et al., 2008b). The accuracy and reliability of these predictive models are of strategic importance to the construction industry for sustained growth and planning purposes.

Forecasting construction output will aid and improve managerial decision making, policy formulation and sustained economic growth. Various time horizons and levels of aggregation are useful for strategic planning. For example, at construction company level, short-term forecast is required for project scheduling and staffing; medium-term forecast for product development, pricing of tenders and marketing; and long-term forecast will be useful for decisions associated with capital investments (e.g. acquisition of new equipment) and exploration of new overseas market. Moreso, governments are interested in construction output due to its linkage with other sectors of the economy. Government intervention programmes during periods of economic recession is crucial to recovery (Goh, 2005, Jiang et al., 2013). Jiang et al. (2013) points out that the anticipated impact of such intervention policies was not achieved in Australia because it was halted too early. The ability to anticipate future trends would ensure the development and implementation of adequate response strategies aimed at reducing the impact of changes in construction output.

The purpose of this paper is to systematically review the current state of empirical literature on construction output forecasting. Although, several studies have tried to differentiate between construction output and construction demand (Goh, 1998). Gruneberg and Folwell (2013) assert that construction component of gross fixed capital formation can be used as a measure of construction output. In contrast, gross value of construction work was used as a measure of construction work (see Goh and Pin, 2000; Fan et al., 2010). Akintoye and Sommerville (1995) show that a lagged relationship exist between construction output and construction demand. It is evident that a thin line of difference exists between construction demand and construction output. Thus, construction demand will eventually filter into construction output. To date, there has been little or no studies focused on a systematic review of construction output forecasting research. Although, an earlier review was done by Fan et al. (2007), the main focus of that review was to identify factors affecting construction demand and the use of exponential smoothing technique to predict construction demand. Hence, this paper presents an up-to-date and more comprehensive review of the construction output literature, briefly discusses advantages and disadvantages of forecasting techniques and evaluates the accuracy of construction output forecast generated by various techniques.

2 Overview of Construction Output Forecasting Techniques

Numerous techniques have been developed for construction output forecasting. In construction-related literature, the earliest work was published by Tang et al. (1990). In this study, regression technique was used to forecast construction (aggregated into residential, nonresidential and other) activities in Thailand. Construction output forecast research has been evolving leading to the use of new techniques. Empirical evidence also confirms that macroeconomic variables are adequate and reliable for developing construction output forecast models (see Goh and Teo, 2000; Jiang and Liu, 2011). The techniques which have been used can be classified into four broad categories (methods) namely: statistical models (SM), structural time-series model (S), artificial neural network (ANN) and hybrid models (H). A detailed discussion on forecasting techniques can be found in the literature (Weron, 2014).

2.1 Statistical Models

Statistical models are based on the mathematical relationship between the dependent variable (current construction output) and a number of independent variables (i.e. determinants), this relationship is either known or estimated (Weron, 2014). Statistical models used in past studies (see Table 1) range from autoregressive integrated moving-average (ARIMA), multiple regression (MR), multiple loglinear regression (MLGR), autoregressive nonlinear regression (ARNLR), vector error correction (VEC), vector error correction model with dummy variables (VEC-D), panel ordinary least squares regression (P-OLS), and panel-vector error correction (P-VEC).

Statistical models can be divided into two subsets namely: stationary process and nonstationary process. Stationary time series possess statistical properties (such as mean, variance, etc.) which are constant over time. In ARIMA class of models, stationary time series is an important process for fitting an ARIMA model and regression models (Goh, 1998). However, the use of co-integration and VEC forecast models ensure that valuable long-term relationship information is not lost during the transformation of non-stationary variables (Anderson and Vahid, 2011). Common to these models, construction output is expressed in terms of its past values and a white noise process. In addition, the parameters for other significant variables can be estimated in multivariate models such as multiple regression.

2.2 Structural Time-series Model

Structural time-series model are quite similar to statistical models. The main difference is that structural time-series model is based on estimating the relationship between trend, seasonal component and noise. Detailed discussions on structural time-series model can be found in Koopman and Ooms (2011).

2.3 Artificial Neural Network

Most of statistical models are linear predictors; however, construction output forecast is known to be a non-linear function of its input features. Thus, statistical models may not adequately predict construction output. In order to solve this problem, researchers have used artificial intelligence techniques such as Artificial Neural Network (ANN), which have the capacity to capture non-linear and complex data structures. Quantitative forecasting is based on the capacity to adequately map between input and output data. ANN possesses the capability to learn past patterns in data and extrapolate underlying patterns, which aids prediction of future outcomes (Shukla et al., 2010). Thus, ANNmay be adequate for forecasting task.

2.4 Hybrid Models

Hybrid methods combine linear and non-linear modelling capabilities, thus, hybrid models complements on the strength and weakness of both approaches. Shukla et al. (2010) acknowledges that hybrid models possess the additional capabilities, which can improve forecast accuracy. An example of hybrid model used in Goh (2000) is an evolutionary ANN, which used genetic algorithm (GA) to evolve ANNs (GA-ANN).

3 Research Method

It is acknowledged that systematic reviews of previous studies extend the general understanding about a research problem. However, the findings of review studies are often questionable due to inexplicit methods (i.e. sampling approach, inclusion criteria, etc.). Although, a generally accepted standard for reporting systematic reviews do not exist; Booth (2006) suggests that the explicit use of STARLITE (STARLITE represents sampling strategy, type of study, approaches, range of years, limits, inclusion and exclusions, terms used and electronic source) will improve on the quality of systematic reviews. Thus, this review adopts a modified version of a method used in similar earlier reviews (Ke et al., 2009; Tang et al., 2010). These earlier reviews were limited to papers published in top-tier construction management journals as classified by (Chau, 1997). The inclusion criterion was modified so as to cover papers published in construction-related journals. As a result, three relevant papers published in Australian Journal of Construction Economics and Building, Building and Environment and Habitat International were obtained from the publisher's database. The process of acquiring papers related to the focus of this review was carried out in 3 stages.

Firstly, a systematic and comprehensive search was conducted under the "title/abstract/keyword" field of SCOPUS database search engine. The full search code is as follows:
TITLE-ABS-KEY ("Construction sector*" OR "construction output" OR "construction industry" OR "construction industry development" OR "construction demand" OR "model" OR "forecasting") AND KEY ("construction" OR "Forecasting")) AND DOCTYPE (ar OR re) AND SUBJAREA (mult OR arts OR busi OR deci OR econ OR psyc OR soci).

Despite these search criteria, the results of the initial search on SCOPUS included some publications that did not meet the study's inclusion criteria. Thus, the search results were scaled down by focusing on papers published in construction-related journals between 1990 and 2014 (years inclusive). In the second stage, a brief review of the abstracts of the papers was conducted; this was done so as to exclude less-related or unrelated papers. In addition, publications classified as “book reviews”, “editorial”, “editor’s notes”, “letter to the editor”, and “articles in press” were excluded.

Finally, after initial filtering, a search in the database of publishers of target journals (this was done because SCOPUS database might not cover some periods in the selected journals) was also done. A total of fifteen articles with relevant content were selected for further analysis.

4 Findings and Discussion

4.1 Number of Selected Papers Annually

The place of construction output forecast in strategic planning has led to studies aimed at developing reliable and accurate predictive models. The earliest published paper amongst those selected for review was published in 1990. As presented in Figure 1, the number of relevant papers published annually was no more than five for the period under consideration. This reveals that construction output forecasting has not received adequate attention. A plausible reason for this might be non-availability of reliable and adequate data, which is essential for model building.

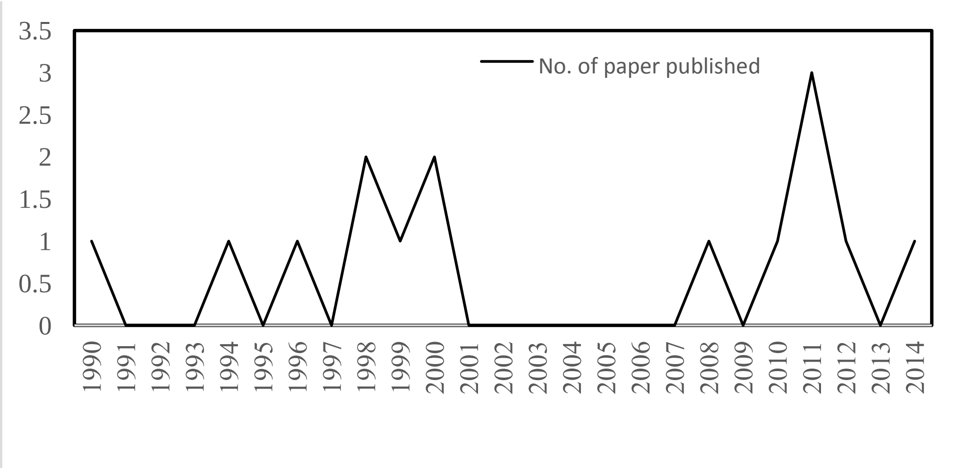

Figure 1. The number of papers distributed annually (from 1990 to 2014)

4.2 Publication Type and Publication Name

In the methods section, the selection criterion was explicitly stated. The search in SCOPUS database and publisher’s database was limited to construction-related journal papers. Table 1 presents the publication names and the corresponding number of published papers. As stated earlier, some of the journals are top-tier construction journals as ranked by Chau (1997), including *Construction Management and Economics and Engineering Construction and Architectural Management*. In addition, some leading construction-related journals are also included, such as *Building and Environment, Habitat International and Australian Journal of Construction Economics and Building*. There were 11 papers from Construction Management and Economics, which comprises 73% of all the selected papers. This demonstrates the significance of Construction Management and Economics in the field of construction output forecasting.

Table 1. Publication names and the number of corresponding papers (1990-2014)

Journal Title	Number
Construction Management and Economics	11
Engineering Construction and Architectural Management	1
Building and Environment	1
Habitat International	1
Australian Journal of Construction Economics and Building	1

4.3 Country/region Distribution

It should be noted that in some previous reviews (Al-Sharif and Kaka, 2004; Ke et al., 2009), country distribution was related to the location of authors affiliated institution. In this review, this has a different meaning; it focuses on where each study was conducted. Five countries/regions from three continents (except Africa, North and South America) were covered as shown in Table 2. This indicates the global focus of construction output forecast studies. With the exception of Thailand, all these studies were focused on developed countries or regions. This clearly highlights the importance attached to the construction industry and the availability of rich database of construction-related statistics, which aids modelling.

Table 2. The number of relevant papers by country/region

Country	Number
Singapore	5
Hong Kong	4
Australia	3
United Kingdom	2
Thailand	1

4.4 Determinants of Construction Output

The determinants (i.e. independent variables) play an important role in the quality of construction output forecast. Determinants of construction output have been classified based on market segment namely: residential, industrial, commercial, public and overall. The significant determinants used along with the class they belong to are presented in Table 3. There are as many as 34 variables used in different studies. Most of the researchers have utilized theory and stepwise regression in selecting variables used in constructing the respective models. Table 3 shows that a diverse range of independent variables have been used in construction output forecast models. A critical look at the variable used as inputs in the studies selected for this review shows that determinants of construction output are unique, i.e. country and context-specific.

Table 3. Significant determinants of construction output

	Dependent Variable (Output)				
Explanatory variables	**Residential**	**Industrial**	**Commercial**	**Public**	**Overall**

Population	TA, G^2, G^3, G^4	G^3			J^1, J^2
GDP/GNP/National Income	A,G^1, N^{sw}	A, G^3	A		N_{fw}, J_1, J_2, F_{NW}
GDP/GNP/National Income per capita	TA, G^1				
Consumer Price	TA, A, G^1, N_{sw}				
Expansion of industrial capacity		TA, G^3			
Expected profits in manufacturing		TA, A	A		
Government revenue/expenditure/ Public construction output				TA	N_{fw}
Value added by public utility				TA,	
Interest rate	A, G^1	G^3	A		J^1, J^2, F^{NW}
Unemployment	G^1, G^2, G^3, G_4, N_{sw}	G^3	A		N^{fw}, J^1, J^2
Gross Fixed Capital Formation	G^1, G^2, G^3				N
Construction material price/Construction tender price index	G^1, G^2, G^3, G^4, F				J^2
Home ownership	G^1				
Saving (personal/national)/ Purchasing Power	G^1, G^2, G^3, G^4	G^3	G^3		J^1
Property Prices	G^1, N^{sw}, F				J^1
Labour force	G^1				
Labour cost		G^3			
Money supply	G^1	G^3			
Housing stock	G^2, G^3				
Housing loan	G^2, G^3				
Planning approval issued/ Additions to housing stock/	G^4, N^{sw}, K		G^3		
Land Price			G^3		
Productivity		G^3	G^3		
Sales (retail,)			G^3		
Investment in manufacturing		G^3			
Export price		G^3			
Volume of exports		G^3			J^1
Exchange rate		G^3			
Leading indicators		G^3			
Availability of Housing loan	G^4				
GFCF (residential)	G^4				
Gross floor area of development commenced	G^T				
Hang Seng Index (stock market index)	N^{sw},				
Value of construction work	F	F	F		F

Note: TA= Tang et al. (1990), A=Akintoye and Skitmore (1994); G1 = Goh (1996); N = Notman et al (1998); G2 = Goh (1998); G3 = Goh (1999); G4 = Goh (2000); GT= Goh and Teo (2000); NSW = Ng et al (2008a); F = Fan et al. (2010); NFW = Ng et al. (2011); FNW = Fan et al. (2011); J1 = Jiang and Liu (2011); K = Karamujic (2012); J2 = Jiang and Liu (2014)

4.5 Construction Output Forecasting Techniques

The complexity, need for accurate forecast and importance of construction output forecast has resulted in the use of several techniques. Based on the classification of forecasting techniques presented earlier, statistical model were the most used techniques in the selected papers, accounting for 79%. The present usage of other techniques: Structural time-series model, Artificial Neural Network and Hybrid models were 4%, 11% and 7% respectively (See Table 4). It is interesting to find that a large majority of the papers used statistical model. This is largely due to its simplicity in use and its ability to estimate the relationship amongst input variables used in the models.

Table 4. Forecasting techniques used in reviewed papers

Author(s) and year of publication	Forecasting tec	Class of technique	Forecast horizon (in quarters)	Type of forecast
Tang et al. (1990)	MR	SM	40	Ex-ante
Akintoye and Skitmore (1994)	MR	SM	12	Ex-post
Goh (1996)	ANN	ANN	3	Ex-post
	MR	SM		
Notman et al. (1998)	ARIMA	SM	3 and 4	Ex-ante and Ex-post respectively
Goh (1998)	ANN	ANN	5	Ex-post
	ARIMA	SM		
	MLGR	SM		
Goh (1999)	MR	SM	5	Ex-post
	MLGR	SM		
	ARNLR	SM		
Goh (2000)	ANN	ANN	5	Ex-post
	GA-ANN	H		
Goh and Teo (2000)	ARIMA	SM	5	Ex-post
Ng et al. (2008a)	LRA	SM	12	Ex-post
	GA-LRA	H		
Fan et al. (2010)			10	Ex-post
	ARIMA	SM		
	MR	SM		
Ng et al. (2011)	VEC	SM	10	Ex-post
	MR	SM		
Fan et al. (2011);	VEC	SM	10	Ex-post
	MR	SM		
Jiang and Liu (2011)	VEC	SM	4	Ex-post
	VEC-D	SM		
Karamujic (2012)	Univariate structural time-series model	S	16	Ex-post
Jiang and Liu (2014)	P-VEC	SM	12	Ex-post
	P-OLS	SM		
	MR	SM		

Note: LRA = Linear Regression Analysis, GA-LRA = Hybrid Genetic Algorithms-Linear Regression Analysis

4.6 Accuracy Comparisons

Studies which compare the accuracy of forecasts of construction output generated by various techniques are presented in Table 5. The selected studies were those focused on out-of-sample forecast. The 10 studies presented in Table 6 presented 12 cases of forecast performance comparison. Statistical forecasting models proves to be the most accurate method in 66.7% of the 12 cases. It was observed that non-linear forecasting techniques tend to generate better outof-sample forecast. Also, back propagation (BP) as the learning algorithm is the most popular choice amongst researchers using ANN for construction output- forecasting problem.

Table 5. Comparison of forecast accuracy

Paper code	Forecasting techniques	Training data (in quarters)	Dependent Variable	Training (%) data (quarters)	Prediction period (quarters)	Level of accuracy	Most accurate technique
G1	ANN	BP	Residential construction	71	3	MPE -0.56 - -1.41 MAPE 1.21 – 1.41	ANN
	ARIMA	-				MPE -6.99; MAPE 6.99	
G2	ANN	BP	Residential construction	72	5	MPE 0.38; MAPE 0.93	ANN
	ARIMA	-				MPE 0.62; MAPE 1.07	
	MLGR	-				MPE 0.58; MAPE 6.34	
G3	MLR	-	Residential construction	72	5	MPE -5.79; MAPE 9.48	MLGR
	MLGR	-				MPE 0.58; MAPE 6.34	
	ARNLR	-				MPE 7.43; MAPE 7.43	
	MLR	-	Industrial construction			MPE 20.67; MAPE 22.42	MLGR
	MLGR	-				MPE -13.32; MAPE 20.82	
	ARNLR	-				MPE 15.64; MAPE 29.66	
	MLR	-	Commercial construction			MPE -58.97; MAPE 58.97	ARNLR
	MLGR	-				MPE -18.79; MAPE -18.79	
	ARNLR	-				MPE 15.24; MAPE 17.33	
G4	ANN	BP	Residential construction	72	5	MPE 0.15 - 0.36; MAPE 0.87 - 0.93	GA-ANN
	GA-ANN	BP				MPE 6.42- 6.92; MAPE 6.42- 6.92	
NSW	LRA	-	Private housing	48	12	IS 62.68; 127.56	GA-LRA
	GA-LRA	-		20		IS 34.69	
	GA-LRA	-		40		IS 31.90	
F	ARIMA	-	Residential construction	87	10	MAPE 4.3	ARIMA
	MR	-		85	12	MAPE 37.6	
FNW	VEC	-	Overall construction	90	10	MAPE 2.33	VEC
	MR	-				MAPE 3.38	
NFW	VEC	-	Private construction	90	10	MAPE 7.5	VEC
	MR	-				MAPE 8.1	
J[1]	VEC	-	Overall construction	51	4	U 0.0262; MAPE 3.58	VEC-D
	VEC-D	-				U 0.0318; MAPE 6.00	
J[2]	P-VEC	-	Regional construction	46	12	U 0.0177 - 0.0450; MAPE 2.89 - 5.43	P-VEC
	P-OLS	-				U 0.0304 - 0.1861; MAPE 7.31-11.43	
	MR	-				U 0.0533 - 0.3675; MAPE 9.95 – 20.05	

Note: mean percentage error (MPE); mean absolute percentage error (MAPE); Theil's inequality coefficient (U); Index Sum (IS)

4.7 *Discussion and a look into the future of 'construction output forecasting'*

Designing of construction output forecast model is a complex task. Variations in significant determinants, forecast horizon, forecasting techniques used, countries/region of study and accuracy assessment have been reported. Although, it was found that statistical models produce most accurate results; this might have occurred due to the over-reliance on such models. It was found that non-linear models (such as ANN, MLGR, etc.) tend to generate more accurate forecast. This was corroborated by the findings of Goh (1999). Marwala (2013) identified the limitation of statistical models to include: linear assumptions, static models, and problems in distinguishing between causality versus correlation. Thus, in order to develop models that can accurately predict construction output, due to its non-linear and complex characteristics. There is a need to further explore the use of non-linear techniques (such as statistical, artificial intelligence and hybrid models) in construction output forecasting research.

The selection of significant determinants (i.e. input variables) is a key issue that affects the success of any forecasting technique. The reliability and adequacy of construction statistics also affects construction output forecast studies. Most studies have used step-wise regression techniques in selecting significant variables for model development. Future studies should consider the use of correlation analysis, principal component analysis (PCA), and similar methods which could further improve performance of out-of-sample forecast.

5 Conclusion and Further Research

It is realized that the reliability and accuracy of construction output forecast can be an effective way to improving planning in the construction industry. The results present a general overview of the trends in construction output forecasting and key issues have been analysed.

In theory several techniques can be used for construction output forecasting; however, in practice just a few of these techniques have been used in empirical literature. The techniques used in construction output have evolved over the last 26 years; it is evident that there have been improvements in model building. One of the interesting findings with respect to statistical models shows that a single model cannot adequately generate forecast for all countries/region/market segment. Hence, it is evident that the construction industry is unique.

Four gaps were identified, namely lack of studies focusing on construction industry in Africa, North and South America; relatively low usage of artificial intelligence techniques despite its ability to adequately capture and forecast non-linearity and complexity associated with construction output data; overlooking of the repair and maintenance sub-sector of the construction industry; and over-reliance on the use of stepwise regression techniques in selecting variables used in model building. Future studies should be targeted at these identified gaps, which will further extend construction output forecasting practice and research.

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